Does bias in the transmission process lead to overestimation of a strategy's value?

Honors Undergraduate Thesis

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By

Brett Bakies
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Thesis Committee:

Dr. Justin Birru

Dr. Joseph Goodman

Dr. Elliot Bendoly

Dr. Thien Nguyen

Abstract

Investors are more likely to speak about their victories in the market as opposed to their defeats, and the listeners of this communication often do not fully discount for the biased sample they are presented. Moreover, if the receivers of this communication do not fully discount the message, it is possible they will overestimate the value of adopting the communicated strategy. Our study tested the presence, strength, and pattern of this bias in the transmission process. Participants in the study allocated a set amount of funds across different securities and had the opportunity to reallocate over multiple rounds. Different information was provided to the participants prior to allocation of the funds in each round. Participants received risk and return tradeoff information and transmissions of biased samples. We examined how the communications of biased samples affect the investment allocations of the participants. A rational economic participant would be expected to allocate most funds in the security with the highest risk and return tradeoff and continue to hold that allocation in the presence of the communications. We found that participants were subject to a transmission bias, causing them to overestimate the value of the biased samples and shift allocations to the securities with the highest transmitted returns. We can conclude individual investors are subject to a transmission bias in everyday interactions that can lead to suboptimal, irrational investment decisions that will cost them in lower returns.

Acknowledgements

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Vita

May 2019…………………………………………BSBA Finance, Max M. Fisher College of Business, The Ohio State University

July 2019………………………………………..Incoming Investment Banking Analyst at Mizuho

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Introduction to Behavioral Finance

Behavioral finance is the marriage of finance with the fields of psychology and sociology. Behavioral finance attempts to explain market movements and anomalies by loosening the assumptions made to justify the Efficient Market Hypothesis (EMH), which states that all asset prices reflect all available information (Hirshleifer, 2014). Therefore, all prices should be correct, and it should be impossible to consistently beat the markets over the long run (Hirshleifer, 2014). For many years, the Efficient Market Hypothesis was considered by many to be the best explanation for how markets work, and many still believe that it is. With the work of Daniel Kahneman, Richard Thaler, Amos Tversky, and Robert Shiller towards the end of the 20th century, behavioral finance was born. The basic implication of the field is that there are irrational aspects of human judgement and behavior that have effects at the individual level and in market prices (Hirshleifer, 2014). Most recently with the growth of the field, many sub-fields have emerged. One such sub-field investigates how cognitive biases effect market participants' decisions at an individual level, and that is what this study looked at.

Introduction to this Research

Psychological biases have major implications for investment performance at the individual level. For example, overconfidence helps to explain how aggressive trading at the individual level reduces welfare, and why individual investors trade actively despite taking losses (Odean, 1998; Barber & Odean, 2000; Hirshleifer, 2014). Much work has been done to investigate psychological biases and their effects. Less work, however, has been done to investigate the effects of bias in social interaction at the individual level. The approach in this research is based on how conversational biases can increase the favorability of a flawed approach in personal investing (Shiller, 1995, 2000). The work specifically looks at bias in the transmission process, deriving motivation from "Self-Enhancing Transmission Bias and Active Investing" (Han & Hirshleifer, 2015). This study aims to investigate the underlying "self-enhancing transmission bias" in social interaction and its impact by testing the conclusions of Hirshleifer and Han (Han & Hirshleifer, 2015). The transmission bias explains that while investors are more likely to speak about their victories in the market as opposed to their defeats, the listeners of this communication do not fully discount for the biased sample they are presented (Han, Hirshleifer, & Walden, 2018). Moreover, if the receivers of this communication do not fully discount the message, it is possible they will overestimate the value of adopting the communicated strategy (Han & Hirshleifer, 2015).

The main question this research attempts to answer is whether this bias in the transmission of a communication can influence investors to act in a less than optimal way. This question is investigated using simple portfolio allocation decisions. Study participants are asked to allocate a portfolio across four securities in the presence of risk-return tradeoff information. This is information a rational investor should use to allocate, by allocating more of the portfolio in the securities with the highest return per unit of risk. However, investors are also provided with communications of other participants' realized returns. This information should be severely discounted by a rational investor, considering no details are provided other than the realized percentage return. No details are provided regarding risk, and this is considered a biased sample. If participants behave rationally, they will discount the information in the biased sample properly, and portfolios will be allocated using the risk-return tradeoff information. If participants are subject to a transmission bias, they will not discount the biased sample properly, they will overestimate the value of the communicated returns, and portfolios will be allocated using the communicated returns. The expectation of the investigator is that participants are subject to a transmission bias. By examining the shifts in portfolio allocations, we can conclude whether the sample was subject to a transmission bias and make inferences across the population. This investigation also examines the relationship between the size of the communicated returns and the shifts in portfolio allocations. Specifically, we examine whether higher communicated returns for a security increase the likelihood of a higher portfolio allocation in that security. The role of demographic information is also briefly examined.

Literature Review

Robert Shiller, a proponent of behavioral finance, once stated, “Investing in speculative assets is a social activity” (Shiller, 1989). Indeed, much evidence has been found in recent years to support Shiller’s statement. Mutual fund managers communicate with each other, and this contributes to herding effects, that result in the managers buying and selling the same securities (Hong, Kubik, & Stein, 2005). Research has found that social networks play an important role in how information flows into market prices (Cohen, Frazzini, & Malloy, 2008). Other work has been done finding that individuals’ investment decisions are influenced by coworkers’ investment performance (Lu & Tang, 2015). If a coworker experiences a higher equity return, an individual is likely to shift a larger portion of their 401k into equities and take on more risk (Lu & Tang, 2015). There’s also significant evidence that the interaction between individuals greatly influences the decision to begin investing in the stock market (Kaustia & Knupfer, 2011; Liu, Meng, You, & Zhao, 2018; Hong, Kubik, & Stein, 2004; Brown, Ivković, Smith, & Weisbenner, 2008).

Perhaps most pertinent to the work done in this paper, empirical research has been done using data collected from social networks to test the conclusions of Hirshleifer and Han (Han & Hirshleifer, 2015). This research found that the likelihood a foreign exchange trader contacted another trader was increasing as their returns were increasing, which follows the insight that investors are more likely to communicate about their successes in the market (Heimer & Simon, 2013). The research also found evidence to support the popularity of active investing. It found that traders were more likely to adopt an active strategy if they had received communications from other traders about the success of such strategies (Heimer & Simon, 2013).

The literature makes it clear that social interaction influences investor behavior and social biases effect individuals' investment decisions and outcomes. This study hopes to add the already existing literature by utilizing a controlled environment to isolate bias in the transmission process.

Methodology

The study was administered through the use of online survey software. Participants were provided with instructions prior to beginning the study. Participants were asked to invest 10,000 across 4 securities in an initial allocation and in two reallocations, referred to as Round 0, Round 1, and Round 2. Risk-return tradeoff information for the 4 securities was provided to the participants in Round 0, 1, and 2. The instructions also stated, "this is a simulated exercise, please note all four securities represent real S&P 500 stocks, and the performance of your decisions will be tracked and analyzed, but your responses will be anonymous." It was explicitly stated to participants that "as a rational economic participant, you like return and dislike risk.", and to "assume the provided risk and return tradeoff information is the long-run constant for each security". Additional information was provided to participants before both Round 1 and Round 2.

Participants were provided with long-term risk-return tradeoff information for 4 securities. Security A, B, C, and D had the best to worst risk-return tradeoff information as can be seen in Figure 1 below. This is the information provided to participants, along with an explanation stating, "Below is information on the securities you may invest in, based on the Return per unit of risk (i.e., the Sharpe Ratio). This is the amount of return an investor sees on average from a security, per unit of the security's risk/volatility. The higher the ratio, the more return is received relative to risk".

Investable security	Return per unit of risk
Security A	2.11
Security B	0.79
Security C	0.54
Security D	-0.65

Figure 1: Risk-return tradeoff information

The study was separated into two groups, a treatment and a control. In both groups, participants are provided with transmissions in Round 1 and Round 2. These transmissions take the form of a communication of another participants' return. It is stated to the participants that a participant in a previous edition of the study received a particular return pattern for each security. The returns for each are provided. This information is synthesized and it represents a biased sample through which we test for transmission bias. In the presence of this information, participants are asked to reallocate their portfolios in both Round 1 and 2.

In the treatment group, the returns provided in the communications in both Round 1 and 2 were the highest for Security D, followed by B, C, and A in order. The Security with the worst long-term risk-return tradeoff, Security D, had the largest return as transmitted to the participant. The Security with the best long-term risk-return tradeoff, Security A, had the worst return as transmitted to the participant. See Figure 2 below for the full list of returns provided to the participants in the treatment group in Round 1 and 2.

Investable security:	Historical return:
Security A	-14.24%
Security B	-2.63%
Security C	-10.13%
Security D	7.40%

Investable security:	Historical return:
Security A	-5.49%
Security B	12.19%
Security C	-5.03%
Security D	19.03%

Figure 2: Treatment Round 1 (left) and Round 2 (right) communicated return

In the control group, the returns provided in the communications in both Round 1 and 2 were the highest for Security A, followed by B, C, and D in order. The Security with the worst long-term risk-return tradeoff, Security D, had the worst return as transmitted to the participant. The Security with the best long-term risk-return tradeoff, Security A, had the best return as transmitted to the participant. See Figure 3 below for the full list of returns provided to the participants in the control group in Round 1 and 2.

Investable security:	Historical return:
Security A	8.93%
Security B	5.14%
Security C	-0.77%
Security D	-1.20%

Investable security:	Historical return:
Security A	4.32%
Security B	2.17%
Security C	-1.90%
Security D	-8.41%

Figure 3: Control Round 1 (left) and Round 2 (right) communicated return

The study was completed online using the survey tool, Qualtrics. The study sampled from two different populations. The study was administered in the Marketing Research Lab (Lab) in the Fisher College of Business and using the Amazon Mechanical Turk (MT). Participants in the Lab were students enrolled at the college with the average age of 20 years old. The MT is a cloud sourcing platform and participants can be anyone, anywhere. The Lab gave 105 observations, each one student. The MT gave 288 observations, each one worker. This includes both the treatment and control groups.

Results

Treatment Group

In the first round of allocation, participants followed the rational expected allocation order as seen in Figure 4 below. They placed most their allocation in Security A, followed by B, C, and D in order. This was expected and required for the results in subsequent rounds to be functional in looking at the bias.

Summary Table Round 0

	Security A	**Security B**	**Security C**	**Security D**
Average Allocation	4363.13	2352.94	1966.44	1317.49
Average % Allocation	43.63%	23.53%	19.66%	13.17%
Average Rank	1	2	3	4
Provided Sharpe Ratio	2.11	0.79	0.54	-0.65
Rank	1	2	3	4

Figure 4: Treatment Round 0 results

In the second round, participants had the opportunity to reallocate their portfolio. Participants were provided new information, taking the form of a transmission of another participant's return in a "previous running of this study". The returns provided to the participants were the largest for Security D, followed by B, C, and A in order. The Security with the worst long-term risk-return tradeoff, Security D, had the largest return as transmitted to the participant. The Security with the best long-term risk-return tradeoff, Security A, had the worst return as transmitted to the participant. A rational economic participant unaffected by transmission bias would discount this message, and we would expect to see little to no change in portfolio allocation.

What we have observed, as expected by the investigators, is a large shift in portfolio allocation towards Security D. After Round 1 Security D was, on average, the largest portion of the participants' portfolios. See Figure 5 below for the full results following Round 1.

Summary Table Round 1

	Security A	Security B	Security C	Security D
Average Allocation	2568.31	2417.12	1482.54	3532.03
Average % Allocation	25.68%	24.17%	14.83%	35.32%
Average Rank	2	3	4	1
Communicated Return	-14.24%	-2.63%	-10.13%	7.40%
Rank	4	2	3	1

Figure 5: Treatment Round 1 results

In the final round, participants again had the opportunity to reallocate their portfolio. Participants were provided with new information. Mirroring the returns communicated in Round 1, returns provided to the participants were the largest for Security D, followed by B, C, and A in order.

What we have observed, as expected by the investigators, is a continued shift towards a portfolio allocated according to the communicated returns. Security A, despite having the dominate long-term risk-return tradeoff, is now only the 3rd largest allocated security. See Figure 6 below for the full results following Round 2.

Summary Table Round 2

	Security A	Security B	Security C	Security D
Average Allocation	2289.12	2831.80	1495.75	3383.33
Average % Allocation	22.89%	28.32%	14.96%	33.83%
Average Rank	3	2	4	1
Communicated Return	-5.49%	12.19%	-5.03%	19.03%
Rank	4	2	3	1

Figure 6: Treatment Round 2 results

We found that portfolio allocations did shift according to transmitted returns, which is what was expected by the investigators. By the end of Round 2, the allocations had not completely shifted to the order of the transmitted returns. Security A was the 3rd largest allocation as opposed to 4th, and Security C was 4th as opposed to 3rd. However, allocation in Security A was trending downward. Interestingly, allocation in Security D retreated slightly in Round 2, despite the affirmation of a dominant transmitted return.

See Figure 7, 8, and 9 below for a summary of the cross-section of allocations and the change in allocations from round to round.

Summary Table

		Security A	Security B	Security C	Security D
Round 0	Average Allocation Round 0	43.63%	23.53%	19.66%	13.17%
	Average Rank	1	2	3	4
	Communicated Sharpe Ratio Round 0	2.11	0.79	0.54	-0.65
	Communication Rank	1	2	3	4
Round 1	Average Allocation Round 1	25.68%	24.17%	14.83%	35.32%
	Average Rank	2	3	4	1
	Communicated Return Round 1	-14.24%	-2.63%	-10.13%	7.40%
	Communication Rank	4	2	3	1
Round 2	Average Allocation Round 2	22.89%	28.32%	14.96%	33.83%
	Average Rank	3	2	4	1
	Communicated Return Round 2	-5.49%	12.19%	-5.03%	19.03%
	Communication Rank	4	2	3	1

Figure 7: Treatment summary table

Allocation Change

	Security A	Security B	Security C	Security D
Round 0				
Round 1	-17.95%	0.64%	-4.84%	22.15%
Round 2	-2.79%	4.15%	0.13%	-1.49%

Figure 8: Treatment change in allocations

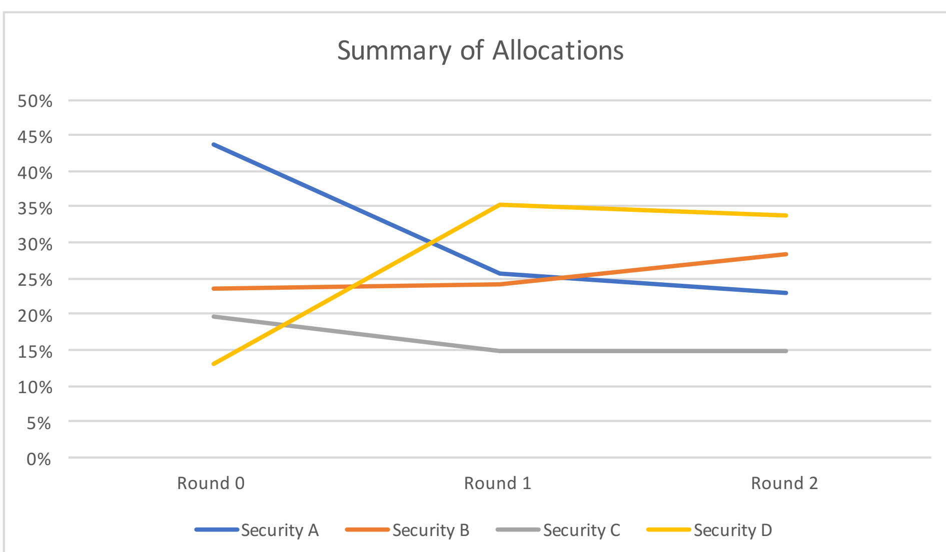

Figure 9: Treatment summary chart

Control Group

The control group received returns that corresponded to the risk-return tradeoff of each security. Security A, B, C, and D had the best to worst risk-return tradeoff information in order, and similarly had the best to worst returns provided to the participant. In other words, participants had no catalyst to deviate from the rational ranking of the portfolio allocations. As expected from the control group, Security A made up most of the portfolio, followed by B, C, and D in order. See Figure 10 below for a summary of the results from the control group.

Summary Table

		Security A	Security B	Security C	Security D
Round 0	Average Allocation Round 0	45.99%	24.22%	18.93%	10.85%
	Average Rank	1	2	3	4
	Communicated Sharpe Ratio Round 0	2.11	0.79	0.54	-0.65
	Communication Rank	1	2	3	4
Round 1	Average Allocation Round 1	62.16%	25.80%	7.07%	4.96%
	Average Rank	1	2	3	4
	Communicated Return Round 1	8.93%	5.14%	-0.77%	-1.20%
	Communication Rank	1	2	3	4
Round 2	Average Allocation Round 2	60.58%	29.86%	5.57%	4.00%
	Average Rank	1	2	3	4
	Communicated Return Round 2	4.32%	2.17%	-1.90%	-8.41%
	Communication Rank	1	2	3	4

Figure 10: Control summary table

Treatment and Control Comparison

Participants' allocations deviated from the optimal rational allocations when subject to the treatment transmissions. These transmissions communicated higher returns for the rationally inferior security, Security D, and lower returns for the rationally superior security, Security A. When subject to the control transmissions, participants' allocations reflected the optimal rational allocations through each round. These transmissions communicated higher returns for the rationally superior security, Security A, and lower returns for the rationally inferior security, Security D. See Figure 11 below for a depiction of the differences between the allocations in Security A and D between the two groups.

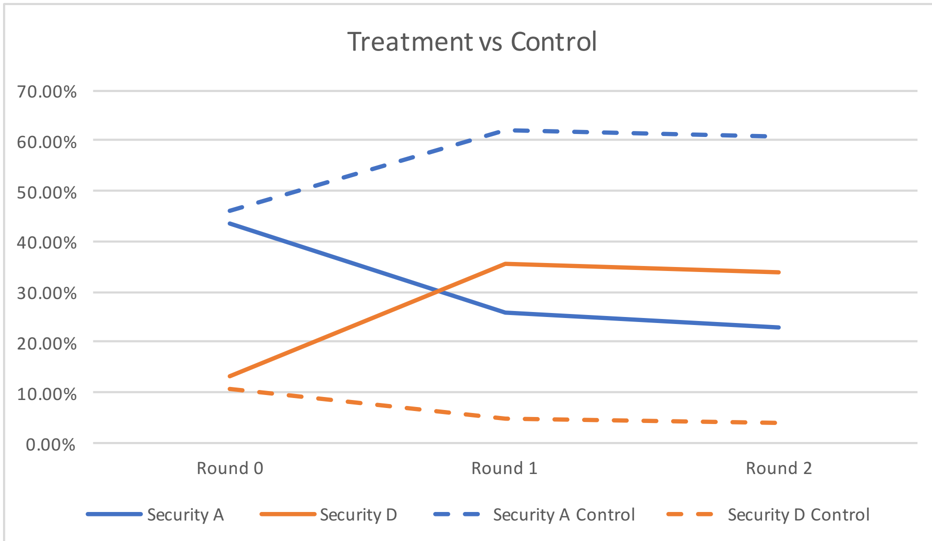

Figure 11: Treatment Security A and D vs Control Security A and D

The differences between the allocations of the control group and those of the treatment were found to be statistically significant for Security A, C, and D in rounds 1 and 2 as shown in Figure 12 below. We would expect the differences to be significant for Security A and D in Round 1 and 2, because in those rounds transmissions are sent giving major deviations in return. In the control group, the transmissions sent in Round 1 and 2 correspond to the initial risk-return tradeoff information. The transmissions give Security A the highest returns and Security D the lowest returns. In contrast, the transmissions sent in Round 1 and 2 in the treatment group give the highest returns to Security D and the worst returns to Security A. Additionally, the returns transmitted in Rounds 1 and 2 for Security B and C were second and third highest, respectively, for both the treatment and control groups. Therefore, it wouldn't be expected to see a significant difference between the control and treatment for either Security B or C.

t-test results (two tail p-value)

	Security A	Security B	Security C	Security D
Round 0	0.44871	0.66529	0.65435	0.23642
Round 1	0.00000	0.60355	0.00000	0.00000
Round 2	0.00000	0.67003	0.00000	0.00000

Figure 12: T-test treatment vs control

Allocations and Transmitted Returns

While only 12 observations, we did find that the portfolio allocations were increasing in sender return. In other words, the higher the transmitted return, the higher the allocation in that security. We also found the trend to be slightly convex. Both were expectations of the investigators. See Figure 13 below. Due mostly to the small number of observations, the results were not significant at the 0.05 level. However, the results were significant at the 0.10 level, which is of note considering only 12 observations. As can be seen in the regression output in Figure 14, a regression gave a p-value of 0.08. The regression output also provides an R-squared statistic of 0.27, giving that only 27 percent of the variance in allocation is explained by the transmitted return. Another depiction of the results can be seen in the line fit plot in Figure 15, which shows above average predictability. The results show that there is a positive relationship present. As the return in the transmissions increase, portfolio allocations towards those respective securities increase. Statistical significance at the 0.05 level may be achieved with an increase in observations.

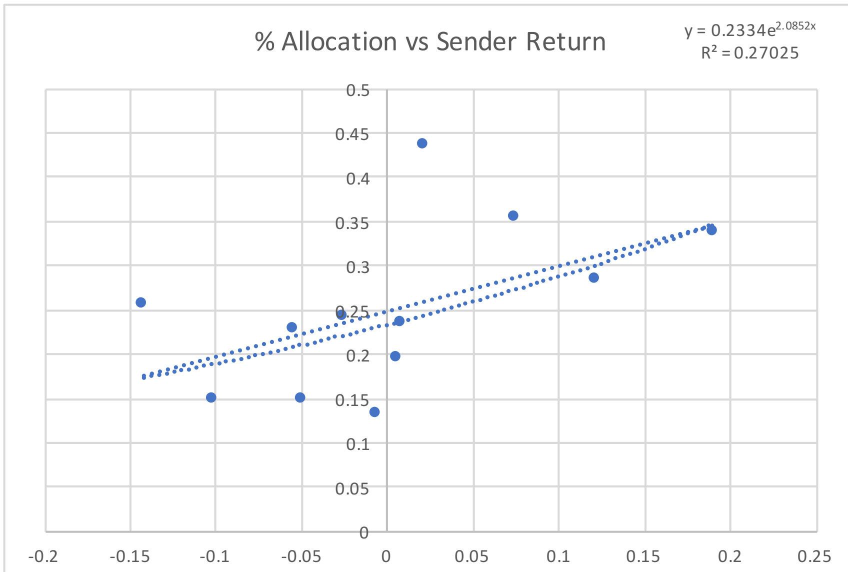

Figure 13: Allocations and transmitted returns chart

Regression Statistics	
Multiple R	0.52179239
R Square	0.2722673
Adjusted R Square	0.19949403
Standard Error	0.08196207
Observations	12

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.025133292	0.02513329	3.74130915	0.081857109
Residual	10	0.067177802	0.00671778		
Total	11	0.092311094			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0.2483218	0.023676313	10.4881958	1.0252E-06	0.195567691	0.30107592	0.19556769	0.30107592
Sender Return	0.51769565	0.267647206	1.9342464	**0.08185711**	-0.07865949	1.11405078	-0.0786595	1.11405078

Figure 14: Allocations and transmitted returns regression

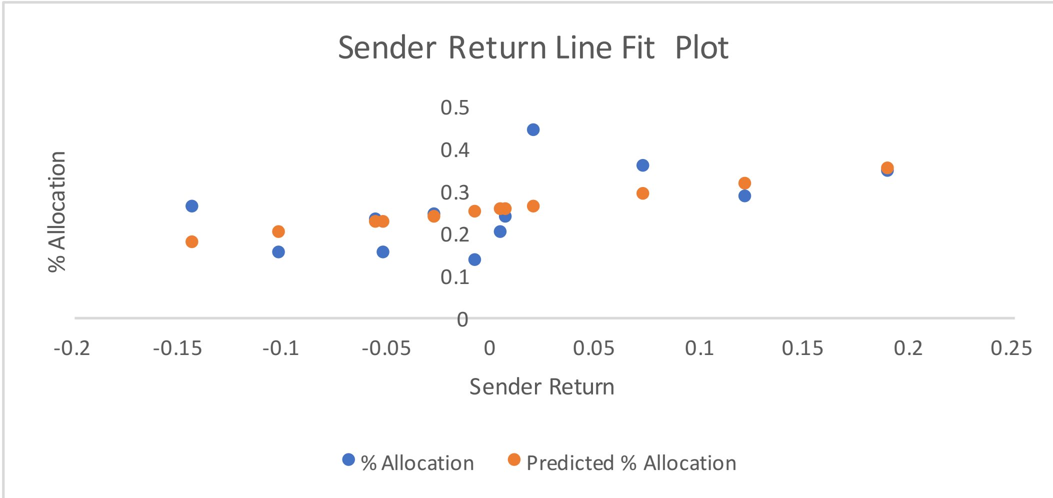

Figure 15: Allocations and transmitted returns line-fit plot

While only 8 observations, we also found that the change in portfolio allocations from round to round were increasing based on the change in sender return. For example, if the transmitted return changed dramatically from round to round, it was likely that the portfolio allocations would also change dramatically. See Figure 16 below. The results were not significant at the 0.05 level, but were significant at the 0.10 level. A clear positive relationship exists. The full regression results can be seen in Figure 17. Again, statistical significance may be improved with an increase in observations.

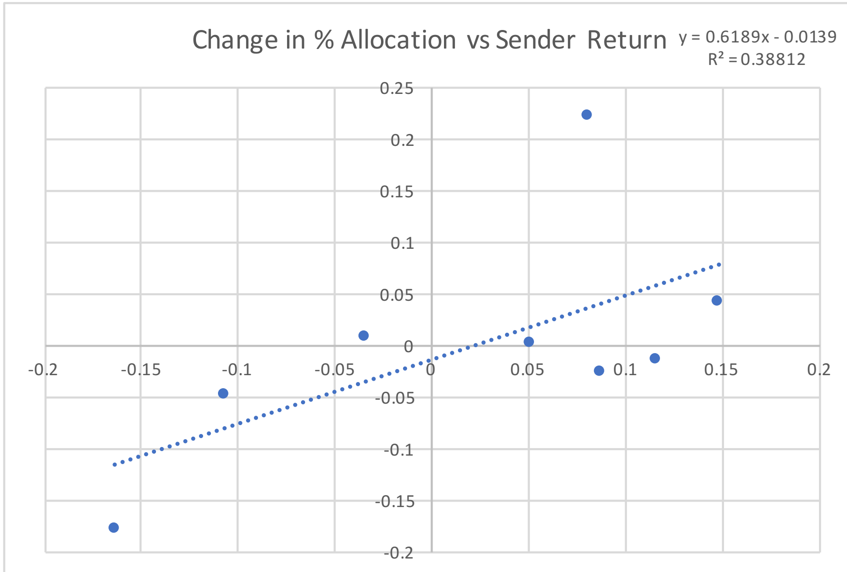

Figure 16: Change in allocations and transmitted returns

Regression Statistics	
Multiple R	0.6229915
R Square	0.38811841
Adjusted R Square	0.28613815
Standard Error	0.09384606
Observations	8

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	1	0.03351816	0.03351816	3.80581884	0.098942191
Residual	6	0.052842494	0.00880708		
Total	7	0.086360654			

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	-0.0138558	0.033931257	-0.4083502	0.69719003	-0.096882629	0.06917096	-0.0968826	0.06917096
Change in Sender Return	0.61890943	0.317251033	1.9508508	**0.09894219**	-0.157375881	1.39519475	-0.1573759	1.39519475

Figure 17: Regression of change in allocations and transmitted returns

Marketing Research Lab and Amazon Mechanical Turk

The study was run through the Marketing Lab at the Ohio State University Fisher College Business (Lab) and online through the Amazon Mechanical Turk (MT). We have found differences in the portfolio allocations of each population as shown in Figure 18. In Round 1 we see the MT participants kept Security A as the 2nd largest allocation in the portfolio, while the Lab participants had Security A as the 3rd largest allocation in the portfolio. The MT participants seemed to be more reluctant to shift the allocations away from the security with the dominant risk-return tradeoff. The differences are significant at the 0.05 level as can be seen in Figure 19.

Summary Table

		Security A	Security B	Security C	Security D
Round 0	Mechanical Turk Allocation Round 0	42.56%	22.41%	20.30%	14.73%
	MT Rank	1	2	3	4
	Lab Allocation Round 0	48.58%	28.74%	16.72%	5.96%
	Lab Rank	1	2	3	4
	Sender Rank Round 0	*1*	*2*	*3*	*4*
Round 1	Mechanical Turk Allocation Round 1	27.33%	23.05%	15.54%	34.07%
	MT Rank	2	3	4	1
	Lab Allocation Round 1	18.14%	29.27%	11.57%	41.02%
	Lab Rank	3	2	4	1
	Sender Rank Round 1	*4*	*2*	*3*	*1*
Round 2	Mechanical Turk Allocation Round 2	24.26%	26.92%	16.22%	32.59%
	MT Rank	3	2	4	1
	Lab Allocation Round 2	16.51%	34.81%	9.07%	39.62%
	Lab Rank	3	2	4	1
	Sender Rank Round 2	*4*	*2*	*3*	*1*

Figure 18: Mechanical Turk vs Lab summary

Security A **Round 1**

	Variable 1	*Variable 2*
Mean	0.18141509	0.26890244
Variance	0.03465998	0.05309287
Observations	53	246
Pooled Variance	0.04986556	
Hypothesized Mean Difference	0	
df	297	
t Stat	-2.5871092	
P(T<=t) one-tail	**0.00507688**	
t Critical one-tail	1.6500003	
P(T<=t) two-tail	**0.01015377**	
t Critical two-tail	1.96798353	

Security B **Round 1**

	Variable 1	*Variable 2*
Mean	0.29273585	0.22678862
Variance	0.04877554	0.02777801
Observations	53	246
Pooled Variance	0.03145435	
Hypothesized Mean Difference	0	
df	297	
t Stat	2.45542186	
P(T<=t) one-tail	**0.00732244**	
t Critical one-tail	1.6500003	
P(T<=t) two-tail	**0.01464489**	
t Critical two-tail	1.96798353	

Figure 19: T-test Mechanical Turk vs Lab

Discussion

In Round 0, participants allocated their portfolios according to the provided long-run risk-return tradeoff information. This information was also provided in the following two rounds. If participants were not subject to a transmission bias, only this risk-return information should've been used to allocate, not the communications of biased samples. However, participants' portfolio allocations did shift in favor of the securities with the highest transmitted returns, which is not what would've been expected of a rational economic participant. We can conclude individual investors are subject to a transmission bias in everyday interactions, as predicted by the investigators and as theorized by Han and Hirshleifer (Han & Hirshleifer, 2015). Implications of this are most easily observable at the individual level. If individuals overestimate the value of converting to the transmitted strategies, they're likely to make suboptimal, irrational investment decisions that will cost them in lower returns. For example, members of investment clubs often communicate about their strategies in the markets and these same members select securities with high beta values, are frequently active investors, and underperform the benchmark (Barber & Odean, 2000; Barber, Heath, & Odean, 2003). Testing the aggregate effects of the transmission bias on the financial markets is incredibly difficult and not much work has been done to investigate how it may be possible. One approach using publicly available data in Chinese provinces shows promise in estimating the effects of social interaction in the aggregate, however, it remains to be seen how individual biases in social interaction could be measured in the aggregate (Liu, Meng, You, & Zhao, 2018).

While it was not found to be statistically significant at the 0.05 level, as a security's transmitted returns increased so did the security's position in the portfolio. In other words, the higher the returns communicated in the biased sample, the more likely participants were to convert to the communicated strategy. This reflects behavior that is the opposite of rational. It also has dangerous implications for individual investors, who are known to communicate often, speak more about their winners than their losers, and overstate their returns (Shiller, 1989; Han & Hirshleifer, 2015; Han, Hirshleifer, & Walden, 2018). Further work should increase the numbers of observations, allowing for a more conclusive decision on the significance of this relationship.

There were differences in allocations between the two sampled populations using Amazon Mechanical Turk (MT) and the Marketing Research Lab (Lab). The biggest difference is in Round 1 between Securities A and B. The participants from the MT were reluctant to allocate less of the portfolio in Security A, which had the dominant risk-return tradeoff. It follows that the bias may have been less prevalent among this group that acted more rationally. This is likely to be attributed to the differences among the demographics of the two groups. We can infer that MT's participants have a higher average age, more life experience, and possibly more experience in the markets than the Lab's student participants that have an average age of 20 years old. This could explain the statistically significant difference in the allocations and the strength of the bias in the two samples. This is an area of consideration for future research.

There are many opportunities for improvement on this research as well as follow up work that can be conducted. One improvement on the current research would be increasing the number of observations. With a deeper data set, the significance of some of the results can be more accurately stated. In addition, demographic factors that were largely not examined in this research could be more closely investigated. For example, we draw a general conclusion that the Mechanical Turk population acted more rationally and we infer that this is due to a higher average age. More data could allow for a more conclusive relationship among age and the effects of the transmission bias. An opportunity for increasing observations could be through collecting data from real interactions of investors on social media platforms which can be seen in *Facebook Finance: How Social Interaction Propagates Active Investing* (Heimer & Simon, 2013). One such social media platform is Matador, a self-proclaimed mobile investing application that allows are users to view buys, sells, and realized returns of anyone in the community (Tap X Trading & Analytics, Inc., 2019). In any follow-up study, another area of improvement will be performance incentives. If a follow-up study focuses on data from a social platform, the incentives are the participants' actual unrealized and realized returns with his or her own capital. If a follow-up study takes place in a controlled laboratory setting or via survey, utilizing performance incentives, such as a cash award for best performance, should work to enhance the results of the study.

As can be seen with the work in this paper, others' work preceding this paper and their work in progress, social interactions can have major implications in investors' decisions and therefore the outcomes of their investments. With continued work on individual level biases like the one investigated in this paper, the hope is to better understand why investors make the decisions they do. Furthermore, the goal is to learn about the forces causing investors to behave irrationally, thereby learning more about why and how markets may behave inefficiently.

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